Detoxification for LLM: From Dataset Itself

Warning: This paper contains and discusses some content that can be offensive or upsetting.

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Abstract

Existing detoxification methods for large language models mainly focus on post-training stage or inference time, while few tackle the **source** of toxicity, namely, the dataset itself. Such training-based or controllable decoding approaches cannot completely suppress the model's inherent toxicity, whereas detoxifying the pretraining dataset can fundamentally reduce the toxicity that the model learns during training. Hence, we attempt to detoxify directly on raw corpora with **SoCD** (**So**ft **C**ontrastive **D**ecoding), which guides an LLM to localize and rewrite toxic spans in raw data while preserving semantics, in our proposed **HSPD** (**H**ierarchical **S**emantic-**P**reserving **D**etoxification) pipeline, yielding a detoxified corpus that can drop-in replace the original for fine-tuning or other training. On GPT2-XL, HSPD attains state-of-the-art detoxification, reducing Toxicity Probability (TP) from 0.42 to 0.18 and Expected Maximum Toxicity (EMT) from 0.43 to 0.20. We further validate consistent best-in-class results on LLaMA2-7B, OPT-6.7B, and Falcon-7B. These findings show that semantics-preserving, corpus-level rewriting with HSPD effectively suppresses downstream toxicity while retaining data utility and allowing seamless source-level mitigation, thereby reducing the cost of later model behavior adjustment.[1]

1 Introduction

Large language models (LLMs) have demonstrated strong performance across a wide range of natural language processing tasks (OpenAI et al., 2024; Yang et al., 2024, 2025; Comanici et al., 2025; DeepSeek-AI et al., 2025; Shi et al., 2025; Zhou et al., 2026). However, the corpora used for LLM pretraining are largely drawn from massive Internet data, which inevitably contain explicit or implicit biases or toxic content; consequently, the model acquires such toxic knowledge during pretraining (Gehman et al., 2020; Webster et al., 2020; Nozza et al., 2021). As a result, LLMs may also generate toxic language, raising concerns about amplifying and disseminating harmful content in real-world settings. Recent studies have examined implicit toxicity in existing LLMs (Wen et al., 2025; Koh et al., 2024), and a growing body of work aims to mitigate toxicity either at inference time (Dale et al., 2021; Xu et al., 2022; Leong et al., 2023; Zhang and Wan, 2023; Zhang et al., 2023) or via post-training interventions (Wang et al., 2022; Park and Rudzicz, 2022; Niu et al., 2024; Lee et al., 2024). Nevertheless, controllable inference methods can degrade generation quality, while post-training approaches often require substantial additional computation. These works in the inference-time and post-training stages can indeed suppress the generation of toxic content to some extent, but it is difficult to fundamentally prevent the model itself from acquiring toxic knowledge learned from the dataset. Therefore, we attempt to approach the problem from another perspective: mitigating the model's intrinsic toxicity from the dataset level, aiming to reduce downstream model toxicity while leaving the model's intrinsic capabilities unchanged.

At the dataset level, prior work has primarily considered dataset distillation (LU et al., 2025); however, distilled data typically still needs to be applied in a post-training stage to induce model-level detoxification. To directly detoxify the dataset, we propose **HSPD** (**H**ierarchical **S**emantic-**P**reserving **D**etoxification) pipeline:

1. Focusing on textual data and perform detoxification by leveraging the model's intrinsic text generation capability together with necessary instructions, we construct prompts that guide the model to rewrite toxic inputs into detoxified text.

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[1]The code can be found at GitHub Repository.

Proceedings of the 64th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 23522–23540
July 2-7, 2026

2. Given that textual semantics can vary substantially, we need to detect potentially toxic content in real time during next-token prediction. We therefore turn to contrastive decoding methods. However, when provided with instruction prompts, classical contrastive decoding methods often struggle to generate outputs that remain semantically close to the original text; accordingly, we apply **SoCD** (**So**ft **C**ontrastive **D**ecoding) to precisely regulate toxic-token logits during large language model decoding, with a finetuned small language model on the toxic dataset, thereby steering generation away from toxic tokens.

3. Finally, to further ensure that the loss of the text's inherent knowledge and characteristics before and after detoxification is minimized, we perform multiple rounds of sampling across several temperatures, and prioritize selecting the detoxified result that is closest to the original text in terms of semantic similarity.

In experiments, we further train GPT2-XL (Radford et al., 2019), LLaMA2-7B (Touvron et al., 2023), OPT-6.7B (Zhang et al., 2022) and Falcon-7B (Almazrouei et al., 2023) on the detoxified corpus to better mimic practical pretraining settings, while also directly evaluating the toxicity of the detoxified text itself. Comprehensive evaluations show that our approach substantially reduces both model toxicity and dataset toxicity, significantly outperforming existing model detoxification methods, while largely preserving the original semantics.

2 Preliminaries

2.1 Toxicity

Definition of Toxicity From the perspective of textual manifestation, toxic content generally refers to unethical statements that contain offensiveness, hate, or bias (Hallinan et al., 2023). It can refer to any rude, disrespectful, or unreasonable speech or behavior that may cause the interlocutor to withdraw from the conversation, and is inherently complex and subjective (Borkan et al., 2019).

Taxonomy of Toxicity We categorize toxicity into two main types: In-Distribution (ID) toxicity and Out-of-Distribution (OOD) toxicity. ID toxicity can be understood as toxic content that a model, after being trained on data labeled as toxic text, is able to recognize and avoid; OOD toxicity refers to toxic content that the model still cannot identify after training, representing toxic knowledge that is not covered in the training corpus. In this paper, our current OOD toxicity primarily refers to "Out-of-Category" generalization across different types of toxicity, rather than a complete "Out-of-Domain" generalization across different data sources.

2.2 Contrastive Decoding

CD (contrastive decoding) (Li et al., 2023; O'Brien and Lewis, 2023) combines an *expert* LM and an *amateur* LM at decoding time to prefer tokens that are likely under the expert but unlikely under the amateur, and both models share the same vocabulary $\mathcal{V}$. Let $s_e(i)$ and $s_a(i)$ denote the unnormalized logits assigned to token $i \in \mathcal{V}$ by the expert and amateur models, respectively.

Contrastive decoding uses two interpretable hyperparameters and operate directly in logit space. Firstly, α**-mask** truncates the candidate set by keeping tokens whose expert probability is at least an α fraction of the expert's maximum probability, which in logit form yields in equation 1:

$$\mathcal{V}_{\text{valid}} = \Big\{ j \in \mathcal{V} : \; s_e(j) \geq \max_{k \in \mathcal{V}} s_e(k) + \log \alpha \Big\}, \tag{1}$$

then β controls the strength of the amateur penalty. The CD logit for token i is showed in equation 2:

$$s_{\text{CD}}(i) = \begin{cases} (1+\beta)\, s_e(i) - \beta\, s_a(i), & i \in \mathcal{V}_{\text{valid}}, \\ -\infty, & \text{otherwise}, \end{cases} \tag{2}$$

followed by standard sampling (optionally with a separate final temperature). The leading $(1+\beta)$ factor decouples the contrastive trade-off from the overall logit scale.

3 Related Work

Detoxification for LLMs Existing detoxification methods can be broadly grouped into four paradigms: (i) *continued training*, including domain-adaptive pretraining, fine-tuning, and RLHF to reduce toxicity (e.g., DAPT (Gururangan et al., 2020)); (ii) *constrained inference*, which steers generation via decoding-time constraints or discriminator guidance, such as gradient-based control (PPLM (Dathathri et al., 2020)), generator–discriminator conditioning (GeDi (Krause et al., 2021)), semantic-preserving rewriting (ParaGeDi

(Dale et al., 2021)), logit-level ensembling (DExperts (Liu et al., 2021)), token replacement with masked LMs (CondBERT (Dale et al., 2021); BERT (Devlin et al., 2019)), and detect–rewrite or self-training pipelines (MARCO (Hallinan et al., 2023), CMD (Tang et al., 2024)); (iii) *prompt-based constraints* that inject safety instructions to induce refusal or safer responses, often studied under jailbreak settings (Xie et al., 2023; Meade et al., 2023; Zheng et al., 2024); and (iv) *knowledge editing*, which localizes toxicity-related components and edits parameters while preserving general abilities (Wang et al., 2024). Recent work also formulates detoxification as dataset-level optimization, e.g., UniDetox (LU et al., 2025) distills datasets (Wang et al., 2018) and leverages contrastive decoding to reduce computational overhead.

In this paper, we follow the common view that *toxicity* comprises offensive, hateful, or biased content (Hallinan et al., 2023) and is inherently subjective (Borkan et al., 2019). We further distinguish *in-distribution* toxicity that can be covered by labeled training corpora from *out-of-distribution* toxicity that remains unrecognized after training, reflecting uncovered toxic knowledge.

Contrastive Decoding Contrastive decoding (CD) (Li et al., 2023; O'Brien and Lewis, 2023) improves generation purely at inference by contrasting an expert model against an amateur model: candidates favored by the expert but not the amateur receive higher scores, often yielding more informative and fluent outputs, especially when the two models differ substantially in scale. Subsequent work extends CD to LLM QA and shows notable gains in abstract reasoning without retraining, partly by reducing pattern-following and reasoning errors (O'Brien and Lewis, 2023).

In this paper, the vanilla contrastive decoding method we use follows the decoding approach proposed by O'Brien and Lewis (2023). However, unlike their formulation, our method completely redesigns the masking strategy to adaptively generate dynamic masks during decoding.

4 Methodology

4.1 Overview

Present detoxification methods for LLMs often exhibit a *safety–utility* tension: aggressive controls can harm fluency or meaning preservation, while conservative controls can leave subtle toxicity intact. We propose a **HSPD** pipeline that prioritizes semantic fidelity while removing toxic content through three coordinated components (figure 1): (i) a prompt that constrains generation into a meaning-preserving *rewriting* regime, (ii) **SoCD**, an adaptive decoding-time logit intervention guided by a disparity signal between a base model and a lightweight toxic model, and (iii) a multi-temperature candidate search with fusion reranking to improve robustness.

4.2 Detoxification Prompt Steering

Prompting provides a pre-decoding constraint that converts detoxification into *meaning-preserving rewriting* rather than unconstrained continuation. Hence, for the original toxic text dataset $\mathbb{D}$, suppose there is a toxic text instance $\boldsymbol{a}$ with $\boldsymbol{a} \in \mathbb{D}$. We design a prompt that guides the model to rewrite the toxic text $\boldsymbol{a}$ into a non-toxic or low-toxicity text (the prompt template and examples are provided in appendix C). Subsequently, we obtain a input instance $\boldsymbol{x}$ for the subsequent pipeline.

4.3 SoCD (Soft Contrastive Decoding)

Toxic Model To capture tokens that may carry toxic semantics in a timely manner during decoding, we first need to train a small language model to produce distributional discrepancies. Here, we directly fine-tune the model using $\mathbb{D}$, obtaining the toxic model $\boldsymbol{\theta}_{\text{toxic}}$.

SoCD (Soft Contrastive Decoding) Next, for the base model $\boldsymbol{\theta}_{\text{base}}$ with the same vocabulary V, we input a detoxification prompt with raw text, which is described as $\boldsymbol{x}$ in section 4.2. Suppose that at decoding step t, we get the token probability distributions output by both models in equation 3:

$$\begin{aligned} \boldsymbol{p}_{\boldsymbol{\theta}_{\text{base}}}(\boldsymbol{x}_{<t}) &= \text{softmax}\big(\boldsymbol{s}\big(x_t \mid \boldsymbol{x}_{<t}; \boldsymbol{\theta}_{\text{base}}\big)\big)\,, \\ \boldsymbol{p}_{\boldsymbol{\theta}_{\text{toxic}}}(\boldsymbol{x}_{<t}) &= \text{softmax}\big(\boldsymbol{s}\big(x_t \mid \boldsymbol{x}_{<t}; \boldsymbol{\theta}_{\text{toxic}}\big)\big)\,, \end{aligned} \tag{3}$$

where $\boldsymbol{s}(x_t \mid \boldsymbol{x}_{<t}; \boldsymbol{\theta})$ denotes the logits score, while $\boldsymbol{p}_\theta(\boldsymbol{x}_{<t})$ denotes the probability distribution obtained after applying softmax function for model $\boldsymbol{\theta}$ under current input $\boldsymbol{x}_{<t}$.

Then we compute the difference between the two at this step, which serves as the strength to suppress toxic dimensions. The normalized disparity α is described in equation 4 under current input $\boldsymbol{x}_{<t}$:

$$\begin{aligned} \delta &= f\Big(\boldsymbol{p}_{\boldsymbol{\theta}_{\text{base}}}(\boldsymbol{x}_{<t}),\, \boldsymbol{p}_{\boldsymbol{\theta}_{\text{toxic}}}(\boldsymbol{x}_{<t})\Big), \\ \alpha &= \frac{\ln(1+\delta)}{1+\ln(1+\delta)}, \end{aligned} \tag{4}$$

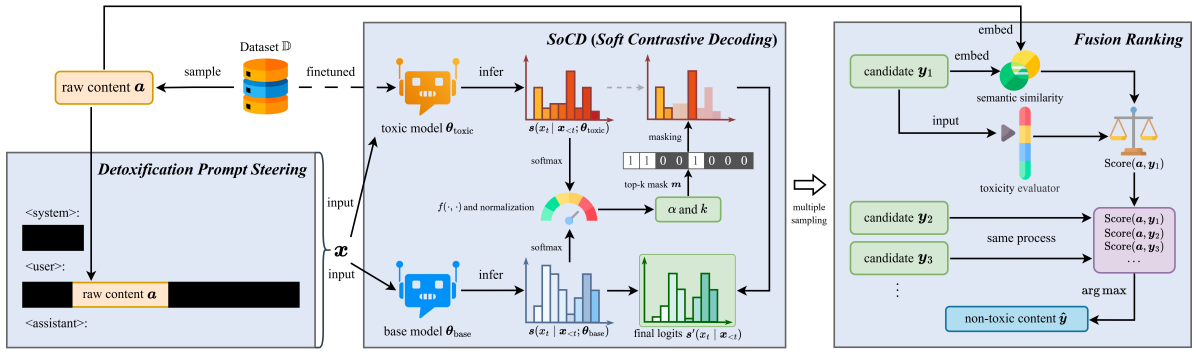

Figure 1: HSPD pipeline overview. Given a toxic input text, we (1) apply a detoxification prompt to rewrite the input, (2) fine-tune a small toxic model and use SoCD (Soft Contrastive Decoding) to adaptively suppress the top-k most divergent (toxic) token dimensions in the base model's logits via a disparity factor α, and (3) sample multiple candidates under different temperatures and re-rank them using a weighted combination of Detoxify-based non-toxicity and embedding-based semantic similarity, selecting the best-scoring output as the final detoxified text.

where $f(\cdot,\cdot)$ denotes a distributional disparity measure (about distribution disparity measures used in this paper, please refer to appendix A.1).

In vanilla contrastive decoding (Li et al., 2023), the aggressive masking of token probabilities often over-suppresses informative dimensions, leading to incoherent or nonsensical generations when detoxifying. To address this, we introduce a revised logit-control constraint that only operates on top-k most divergent dimensions and preserve the remaining dimensions to retain as much information as possible.

For the computation of k, we want the model to adaptively adjust it based on the magnitude of the difference in logits. Therefore, we set k as written in equation 5:

$$k = \alpha \times V. \tag{5}$$

To avoid extreme cases (e.g., $\alpha \approx 0$ leading to $k = 0$ or $\alpha \approx 1$ leading to the entire vocabulary being suppressed), we apply lower and upper bound clipping in practice in equation 6:

$$k = \text{clip}\big(\lceil \alpha V \rceil,\ k_{\min},\ k_{\max}\big), \tag{6}$$

where $1 \le k_{\min} \le \lceil \alpha V \rceil \le k_{\max} \le V$.

Based on the above setup, we further elaborate on the details of SoCD. At step t, we first compute the per-token logits score difference in equation 7:

$$\boldsymbol{d} = \log(\boldsymbol{p}_{\boldsymbol{\theta}_{\text{toxic}}}(\boldsymbol{x}_{<t})) - \log(\boldsymbol{p}_{\boldsymbol{\theta}_{\text{base}}}(\boldsymbol{x}_{<t})), \tag{7}$$

we then set the negative entries in $\boldsymbol{d}$ to $-\infty$, ensuring that the subsequent steps only operate on tokens preferred by the toxic model in equation 8:

$$\boldsymbol{d}_i = \begin{cases} \boldsymbol{d}_i & \text{if } \boldsymbol{d}_i > 0, \\ -\infty & \text{otherwise.} \end{cases} \tag{8}$$

Formally, let $\mathcal{V} = \{1, \ldots, V\}$ be the set of vocabulary indices. To precisely isolate the token dimensions with significant semantic divergence, we identify the subset of indices $\mathcal{I}_k \subset \mathcal{V}$ corresponding to the top-k largest values in the difference vector $\boldsymbol{d}$. This selection process is formulated as an index mapping operation described in equation 9:

$$\mathcal{I}_k = \underset{i \in \mathcal{V}}{\text{argtop}k}\ (\boldsymbol{d}_i), \quad \text{s.t.} \quad |\mathcal{I}_k| = k. \tag{9}$$

Subsequently, we construct a sparse binary mask vector $\boldsymbol{m} \in \{0,1\}^V$ to explicitly target these high-risk dimensions. The i-th component of $\boldsymbol{m}$ is defined using the indicator function $\mathbb{I}(\cdot)$, ensuring that only the selected dimensions are suppressed in equation 10:

$$m_i = \mathbb{I}(i \in \mathcal{I}_k) = \begin{cases} 1, & \text{if } i \in \mathcal{I}_k, \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

By applying this mask, we ensure that the intervention is strictly confined to the dimensions where the toxic model diverges most significantly from the base model.

Finally, for the base model, combined with α, we subtract the absolute value of each element in the toxic model logits obtained via mask-based selection. The final logits are computed as shown in equation 11:

$$\begin{aligned} \boldsymbol{s}'(x_t \mid \boldsymbol{x}_{<t}) = \boldsymbol{s}(x_t \mid \boldsymbol{x}_{<t}; \boldsymbol{\theta}_{\text{base}}) \\ - \alpha\, \boldsymbol{m} \odot \text{abs}(\boldsymbol{s}(x_t \mid \boldsymbol{x}_{<t}; \boldsymbol{\theta}_{\text{toxic}}))\,. \end{aligned} \tag{11}$$

We avoid manually tuning hyperparameters in vanilla contrastive decoding by using the distributional disparity α as an adaptive control signal. A

larger α indicates that the toxic and base models diverge more on the next-token distribution, typically reflecting higher toxicity risk. Accordingly, α determines both the number of intervened dimensions (i.e., k) and the suppression magnitude per selected dimension. Therefore, α jointly specifies "**how much to change**" and "**how aggressively to change**," enabling SoCD to suppress toxic-token dimensions while preserving information in the remaining dimensions.

4.4 Fusion Ranking

A single temperature may not reliably yield outputs that are both safe and faithful: low τ can preserve harmful patterns, whereas high τ increases exploration but may introduce fluency issues or semantic drift. We therefore sample candidates under multiple temperatures and re-rank them with a fused objective. For each input text $\boldsymbol{a}$, we sample a set of candidate detoxified texts under multiple temperatures $\tau \in \mathcal{T}$ with equation 12:

$$\mathcal{C}(\boldsymbol{a}) = \bigcup_{\tau \in \mathcal{T}} \Big\{ \boldsymbol{y} \sim \boldsymbol{p}_\theta(\boldsymbol{y} \mid \boldsymbol{a}; \tau) \Big\}. \tag{12}$$

For each candidate $\boldsymbol{y} \in \mathcal{C}(\boldsymbol{a})$, we compute (i) a toxicity score $t(\boldsymbol{y}) \in [0, 1]$ using the Detoxify classifier (Laura Hanu and Unitary, 2025), and (ii) a semantic similarity score between $\boldsymbol{a}$ and $\boldsymbol{y}$ based on cosine similarity in an embedding space in equation 13:

$$\begin{aligned} s(\boldsymbol{a}, \boldsymbol{y}) &= \cos\big(g(\boldsymbol{a}),\, g(\boldsymbol{y})\big) \\ &= \frac{g(\boldsymbol{a})^\top g(\boldsymbol{y})}{\|g(\boldsymbol{a})\|\, \|g(\boldsymbol{y})\|}, \end{aligned} \tag{13}$$

where $g(\cdot)$ is a text embedding model, and we use Qwen3-Embedding model (Zhang et al., 2025) throughout. We then define the re-ranking objective as a weighted combination of *non-toxicity* and semantic similarity in equation 14:

$$\begin{aligned} \text{Score}(\boldsymbol{a}, \boldsymbol{y}) = \lambda\big(1 - t(\boldsymbol{y})\big) + (1 - \lambda)\, s(\boldsymbol{a}, \boldsymbol{y}), \\ \lambda \in [0, 1], \end{aligned} \tag{14}$$

and select the final detoxified output by equation 15:

$$\hat{\boldsymbol{y}} = \arg\max_{\boldsymbol{y} \in \mathcal{C}(\boldsymbol{a})} \text{Score}(\boldsymbol{a}, \boldsymbol{y}). \tag{15}$$

Subsequently, we obtain $\hat{\boldsymbol{y}}$ as a substitute non-toxic text for $\boldsymbol{a}$.

5 Experiment

5.1 Datasets and Models

Datasets We use the Dynamically Generated Hate Speech (DGHS) (Vidgen et al., 2021) dataset as the input corpus for training the toxic model as well as for the final detoxification process; it contains a large number of harmful statements targeting different social groups. For evaluation, we use the ToxiGen (Hartvigsen et al., 2022) dataset, which includes explicitly or implicitly toxic statements toward various groups. To measure how our detoxification method performs differently on in-distribution toxicity versus out-of-distribution toxicity, we also split the DGHS dataset and use only the categories of *gender*, *sexual orientation*, *race*, and *religion* for training and detoxification, treating these toxicity categories as in-distribution toxicity. The ToxiGen dataset, on top of covering the above categories, additionally includes the *physical and mental disabilities* category, which we use to evaluate the model's detoxification performance on out-of-distribution toxicity. Furthermore, we use the MMLU (Hendrycks et al., 2021) dataset to evaluate the model's downstream performance after detoxification.

Models For model selection, we use Qwen2.5-0.5B (Yang et al., 2024) as the toxic model, and Qwen2.5 models of 0.5B, 3B, and 7B parameters as the base models. To assess detoxification effectiveness, following common practice, we use GPT2-XL (Radford et al., 2019), LLaMA2-7B (Touvron et al., 2023), OPT-6.7B (Zhang et al., 2022) and Falcon-7B (Almazrouei et al., 2023). We **fine-tune them on our detoxified text** and examine the resulting performance separately.

For training the toxic small model Qwen2.5-0.5B, we likewise use the same categories from the DGHS dataset for detoxification, and conduct continuous pretraining using ms-swift (Zhao et al., 2025), and the detailed training hyperparameters are provided in appendix A.2.

5.2 Baselines

The baseline methods are mainly divided into three categories. The first category performs detoxification using prompts only; the second category performs detoxification using a combination of prompts and vanilla contrastive decoding; the third category consists of currently known public algorithms. The vanilla contrastive decoding method

in the second category adopts the parameter settings in O'Brien and Lewis (2023). For the third-category baselines, we select DExperts (Liu et al., 2021), LM-Steer (Han et al., 2024), and UniDetox (LU et al., 2025) as references; brief introductions and parameter settings for each algorithm can be found in appendix A.1.

5.3 Metrics

Based on prior work, we finetuned GPT2-XL, LLaMA2-7B , OPT-6.7B and Falcon-7B on our detoxified texts, and mainly evaluate the post-detoxification effects along three aspects: toxicity mitigation, language modeling ability, and downstream task performance.

Mitigating Toxicity In line with prior studies (Gehman et al., 2020; Liu et al., 2021; Zhang and Wan, 2023; Leong et al., 2023; Han et al., 2024), we sample 25 continuations (up to 20 tokens each) for every ToxiGen example using nucleus sampling with $p = 0.9$ (Holtzman et al., 2020). We evaluate toxicity with Detoxify using two measures: (1) **Toxicity Probability (TP)**, the observed chance that at least one of the 25 generations attains a Detoxify score > 0.5; and (2) **Expected Maximum Toxicity (EMT)**, the highest Detoxify score recorded across the 25 generations. In detoxification tasks, this class of metrics can also serve as our **core metrics**.

In addition, we provide an explanation of the **ID** and **OOD** metrics: ID refers to the toxicity categories filtered from DGHS, and is used to measure the model's detoxification performance on known toxicities; OOD refers to toxicity categories that do not belong to ID, and is used to measure the model's generalization ability for detoxification.

Language Modeling Capability Consistent with prior work (Liu et al., 2021; Zhang and Wan, 2023; Han et al., 2024), we gauge language modeling along two axes: (1) **Perplexity (PPL)** computed by LLaMA2-7B to reflect textual fluency; and (2) **Dist-1/2/3**, the average numbers of unique uni-, bi-, and trigrams, normalized by output length, aggregated over 25 generations per prompt to quantify diversity. These metrics will serve as our **reference metrics**, primarily assessing the impact of the detoxification process on the model's generative capability.

Downstream Task Performance Building on earlier evaluations (Brown et al., 2020), we assess downstream capability on MMLU and report **Accuracy (Acc.)**: 1-shot accuracy for models. This metric will serve as a reference indicator for assessing the impact of our detoxification process on the model's performance on downstream tasks.

Direct Toxicity Scores As our generated corpus preserves the semantics of the original text, we measure the reduction in direct toxicity scores across each toxicity evaluation dimension. Finally, the mean value is computed over all texts in the dataset. We use Detoxify to directly score the detoxified outputs across multiple dimensions and compare how prompt engineering, vanilla contrastive decoding, and SoCD suppress toxicity. This metric is mainly used for the parameter sensitivity study (see section 5.6).

5.4 Results

In this section, we use the Qwen2.5 series models (Yang et al., 2024) throughout to detoxify texts. The toxic model has a 0.5B-parameter scale, and the base models are 0.5B, 3B, and 7B in size. In the subsequent detoxification fine-tuning process, we use the GPT2-XL model for fine-tuning training to evaluate toxicity.

Detoxification results among models We mainly focus on the DGHS dataset to evaluate the extent to suppress model toxicity.

In table 1, we present the results of the HSPD pipeline and other baselines, where the distributional divergence measure is measured using the EMD (earth mover's distance) and $\lambda = 0.5$ in equation 14 with **SoCD**. The results are obtained under the setting where the base model is Qwen2.5-3B and the toxic model is Qwen2.5-0.5B. The results are averaged over five runs with different random seeds, with both the mean and standard deviation presented. The in-distribution (ID) scores capture Toxicity Probability (TP) and Expected Maximum Toxicity (EMT) on domains directly used for detoxification, while the out-of-distribution (OOD) scores reflect the model's ability to generalize detoxification performance to unseen domains. For baselines denoted by model names, we directly perform inference using the original model.

It can be observed that our detoxification method substantially outperforms baseline methods such as UniDetox on toxicity metrics. Although it sacrifices a certain degree of text quality, it ensures leading performance on the primary toxicity metrics and still preserves the model's capabilities on downstream tasks.

Table 1: **Detoxification results across models**. Scores are reported as the average across five runs. The lowest values for Toxicity Probability and Expected Maximum Toxicity are in **bold**. HSPD produces detoxified texts that yield the best detoxification effectiveness for subsequent model training.

Model	Core Metrics				Reference Metrics				
	TP (↓)		EMT (↓)		PPL (↓)	Diversity (↑)			Acc. (↑)
	ID	OOD	ID	OOD		Dist-1	Dist-2	Dist-3	1-shot (%)
GPT2-XL	0.54	0.40	0.54	0.41	17.53	0.26	0.43	**0.46**	**31.81**
LM-Steer	0.42	0.33	0.43	0.36	19.44	**0.28**	0.42	0.45	29.72
DExperts	0.48	0.36	0.49	0.38	18.12	0.27	**0.44**	**0.46**	30.83
UniDetox	0.42	0.25	0.43	0.30	**11.30**	0.20	0.33	0.37	31.61
HSPD (Ours)	**0.18**	**0.19**	**0.20**	**0.22**	21.45	0.16	0.22	0.22	30.83
LLaMA2-7B	0.59	0.55	0.58	0.55	7.46	0.25	**0.41**	**0.44**	40.89
LM-Steer	0.46	0.41	0.46	0.40	11.62	**0.28**	0.35	0.38	**41.02**
DExperts	0.45	0.36	0.46	0.38	10.57	0.27	0.40	0.42	37.75
UniDetox	0.28	0.25	0.30	0.28	**7.04**	0.18	0.22	0.27	38.67
HSPD (Ours)	**0.16**	**0.18**	**0.21**	**0.22**	18.42	0.15	0.21	0.21	38.60
OPT-6.7B	0.79	0.84	0.77	0.81	16.67	0.25	**0.42**	**0.45**	34.10
LM-Steer	0.75	0.80	0.70	0.76	22.35	0.25	0.41	0.43	30.83
DExperts	0.60	0.59	0.61	0.62	26.71	**0.26**	0.38	0.40	**35.62**
UniDetox	0.26	**0.18**	0.31	**0.21**	**10.94**	0.19	0.30	0.31	30.64
HSPD (Ours)	**0.16**	0.19	**0.21**	0.24	22.87	0.17	0.25	0.26	32.79
Falcon-7B	0.59	0.56	0.58	0.54	**10.72**	0.26	**0.43**	**0.46**	**39.26**
LM-Steer	0.39	0.33	0.40	0.34	28.47	0.25	0.34	0.36	34.49
DExperts	0.29	0.25	0.36	0.26	28.19	**0.28**	0.39	0.40	36.83
UniDetox	0.31	0.28	0.36	0.31	10.74	0.16	0.23	0.26	34.67
HSPD (Ours)	**0.13**	**0.15**	**0.18**	**0.20**	24.96	0.15	0.21	0.21	35.08

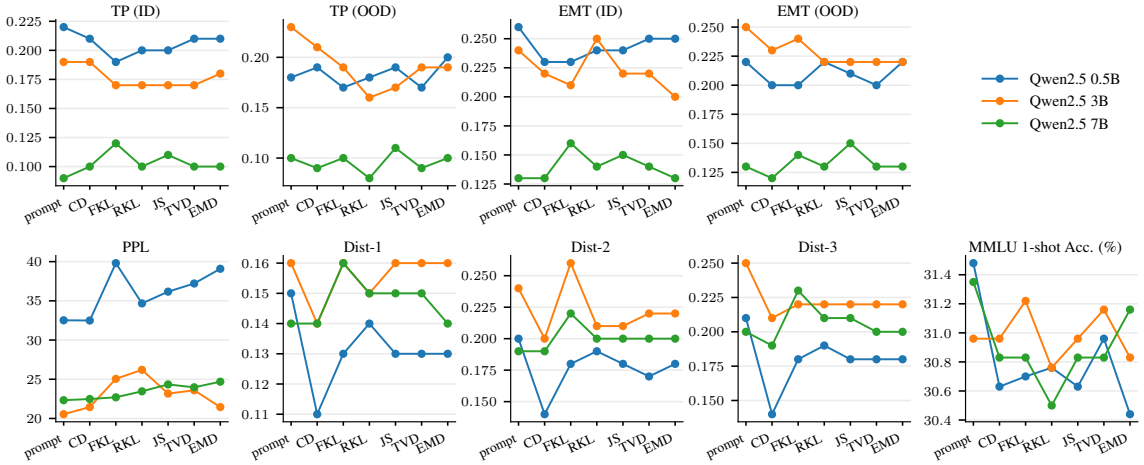

Figure 2: **Differences resulting from different distribution divergence measures**. We report the toxicity evaluation results of a GPT2-XL model trained on detoxified texts obtained under different base model parameter scales and different distribution divergence measures. With larger-scale base models, detoxification effect is not pronounced, whereas with smaller-scale base models, a certain degree of detoxification improvement can be achieved.

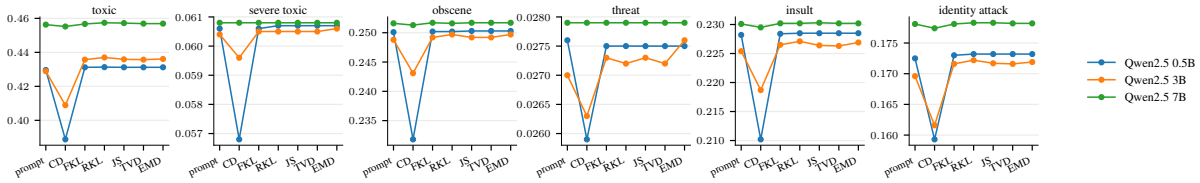

Figure 3: **Direct toxicity scores** of base models on original texts across different parameter scales. As shown, our pipeline achieves a certain improvement in detoxification effectiveness on smaller-scale models.

Table 2: **Ablation study of HSPD based on GPT2-XL**. In addition to the conventional metrics for model toxicity, **Sim.** metric is introduced to represent the average cosine similarity between the detoxified and original texts. SoCD significantly reduces toxicity, whereas Fusion Ranking focuses on maximally preserving the original semantics.

Model	Core Metrics				Reference Metrics					
	TP (↓)		EMT (↓)		PPL (↓)	Diversity (↑)			Acc. (↑)	Sim. (↑)
	ID	OOD	ID	OOD		Dist-1	Dist-2	Dist-3	1-shot (%)	
GPT2-XL	0.54	0.40	0.54	0.41	17.53	0.26	0.43	0.46	31.81	——
w/o SoCD or FR, s=1	0.48	0.38	0.48	0.43	15.82	0.20	0.30	0.32	31.09	0.8449
w/o SoCD, s=3	0.48	0.40	0.47	0.43	15.34	0.21	0.32	0.34	31.03	0.8655
w/o FR, s=1	0.26	0.29	0.27	0.30	15.89	0.18	0.28	0.32	31.03	0.8469
s=3	0.28	0.30	0.29	0.30	16.45	0.19	0.29	0.32	30.83	0.8685

About SoCD, we further compare the detoxification performance on LLaMA2-7B, OPT-6.7B, and Falcon-7B. The advantages of SoCD are not "unconditionally consistent" across all models and distributions: for instance, in the OOD setting of OPT-6.7B, SoCD's gains are more concentrated on the ID set. This suggests that the benefits of SoCD may depend more on the "consistency between training and evaluation distributions", and that cross-domain generalization can still be affected by the base model's generation preferences and the coverage of the toxicity domain. We also observe that our method achieves effects similar to those for detoxifying GPT2-XL: it significantly outperforms the baselines on the main toxicity metrics, yields lower text quality than the baselines, and largely preserves downstream task capability. Further analysis for the outputs of detoxified models are provided in appendix B.3.

Detoxified Text Analysis In this section, we analyze the quality of the detoxified texts generated by our HSPD method, as presented in table 1. First, we evaluate text diversity using the Dist-1/2/3 metrics. As shown in table 3, compared to the original texts, it can be observed that the text shows a decrease in the Dist-1 metric, indicating vocabulary contraction. This is expected, as the detoxification process removes a substantial amount of "long-tail toxic vocabulary" and "non-standard spellings." Conversely, the increases in the Dist-2 and Dist-3 metrics suggest that the syntactic structures have become richer; the detoxification process utilizes standard vocabulary to form diverse sentence structures to convey the detoxified meaning. Additionally, the average sentence length of the detoxified text actually increased. We also analyze the vocabulary composition and the occurrence of templated responses before and after text detoxification; further details are provided in appendix B.2.

Table 3: **Detoxified text diversity analysis**. Scores of Dist-1/2/3 are reported below. **Length** denotes the length of the detoxified text, **Avg.** indicates the average length, and **Med.** refers to the median length. Following detoxification, the Dist-1 score decreases slightly, whereas the Dist-2/3 metrics show an increase, and the average sentence length of the detoxified text remains.

Text	Diversity (↑)			Length	
	Dist-1	Dist-2	Dist-3	Avg.	Med.
Original	0.0513	0.3800	0.7237	34.03	25.0
Detoxified	0.0453	0.3890	0.7415	35.55	28.0

In summary, the detoxified text can be viewed as a semantic-preserving rewrite where the actual text quality has improved, establishing a solid foundation for the subsequent detoxification training.

5.5 Ablation Study

In this section, we primarily investigate the contribution of each HSPD module to the detoxification process. For an intuitive comparison, we reuse the HSPD method presented in table 1 and conduct ablation studies on GPT2-XL. Throughout this section, we set the sampling temperature to 0.7, which aligns with the recommendation by Qwen2.5 (Yang et al., 2024). We have designed the following four sets of experiments for the ablation validation:

1). **w/o SoCD or FR, s=1**: Utilizes only prompting, without the SoCD or Fusion Ranking (FR). The sampling temperature for both the toxic and base models is set to 0.7, with the sample size of 1 (s=1).

2). **w/o SoCD, s=3**: Utilizes prompting and Fusion Ranking, without SoCD. The sampling temperature for both the toxic and base models is set to 0.7, with the sample size of 3.

3). **w/o FR, s=1**: Utilizes prompting and the SoCD, without Fusion Ranking. The sampling temperature for both the toxic and base models is set to 0.7, with the sample size of 1.

4). **s=3**: Utilizes prompting, the SoCD and Fusion Ranking. The sampling temperature for both the toxic and base models is set to 0.7, with the sample size of 3.

As illustrated in the table 2, the specific contributions of each module within the HSPD framework can be clearly observed under these varying settings. The application of SoCD leads to a substantial reduction in toxicity scores. While the subsequent use of Fusion Ranking results in an increase in toxicity scores, the semantic information and text fluency preserved after the filtering process contribute to enhancing the model's text generation diversity compared to relying solely on the SoCD approach.

5.6 Parameter Sensitivity Study

In this section, we investigate how equation 4 affects detoxification performance when applied to base models of different parameter scales under HSPD pipeline. Here, we use abbreviations for each distributional divergence measure in SoCD of HSPD (please refer to appendix A.1 for the complete definitions corresponding to each shorthand). We mainly use Qwen2.5-0.5B as toxic model, and perform text detoxification with base models Qwen2.5-0.5B, Qwen2.5-3B, and Qwen2.5-7B. We then evaluate (i) the toxicity behavior of GPT2-XL trained on the detoxified texts produced under different settings, and (ii) the mean absolute decrease, also **Direct Toxicity Scores**, in the detoxification score as assessed directly by Detoxify.

Differences Resulting from Different Distributional Divergence Measures In addition, as shown in figure 2, we evaluate detoxification performance on GPT2-XL, using different distributional divergence measures and different detoxification model sizes. We observe that, regardless of the specific divergence measure, the resulting detoxification effectiveness is similar. For pairs of small toxic models and small base models, introducing the toxic model and contrastive decoding actually degrades the quality of the generated text. For medium-size base models combined with small toxic models, we see clear gains from HSPD with SoCD, accompanied by a slight decline in text quality. For large base models combined with small toxic models, contrastive decoding is nearly ineffective and slightly reduces text quality. At a macro level, detoxification effectiveness increases with the size of the base model, while text quality remains roughly unchanged. In appendix B.1, we additionally provide the results of model toxicity evaluations for LLaMA2-7B, OPT-6.7B, and Falcon-7B under different distribution divergence measures, conducted on texts detoxified using Qwen2.5-3B as the base model.

Direct Toxicity Evaluation From figure 3, in direct toxicity evaluation, we observe that for medium-scale and small-scale models, HSPD outperforms prompt engineering and vanilla contrastive decoding across multiple distribution divergence metrics, and differences in how the distribution divergence is measured have little impact on detoxification. Likewise, as the base model size increases, the degree of toxicity reduction tends to become similar across the various methods.

In summary, we observe that the distribution metric itself does not directly determine the detoxification performance; rather, it indicates that the mechanism of adaptively adjusting the suppression strength based on distributional differences is effective for text detoxification. In addition, smaller models often yield considerable detoxification gains, narrowing the gap between small-scale and large-scale models. In practical engineering deployment, one may prefer evaluation metrics that are more computationally stable and less costly.

6 Conclusion

We study corpus-level detoxification prior to model training, aiming to eliminate toxicity at the source via the HSPD pipeline. Unlike vanilla contrastive decoding that suppresses non-target information, we adopt SoCD to preserve useful content and leverage semantic embeddings to maintain semantic consistency while detoxifying the corpus. Experiments show that the detoxified data slightly degrades generation quality but substantially reduces LLM toxicity, with negligible impact on downstream performance. The resulting corpus can be directly used for pretraining or finetuning without additional detoxification, highlighting the effectiveness of raw-text detoxification for model safety, and reducing subsequent alignment costs.

Limitations

This work still has limitations, mainly reflected in the degradation of text quality: stronger detoxification constraints may cause the generation distribution to contract, making outputs more conservative or template-like, thereby reducing expressive diversity, increasing perplexity, and, in some cases, weakening the original tone, style, and fine-grained semantics (e.g., sarcasm, emotional intensity, and rhetorical expression), leading to pragmatic shifts. In addition, our current analysis of quality changes relies primarily on automatic metrics, lacking more systematic human evaluation to further disentangle degradation patterns across dimensions such as semantic faithfulness, stylistic consistency, and naturalness. Besides, our current definition of In-Distribution (ID) and Out-of-Distribution (OOD) toxicity relies primarily on the division of "toxicity categories" rather than a strict "data domain shift", and cross-domain generalization can still be affected by the base model's generation preferences and the coverage of the toxicity domain. In the future, we will explore finer-grained, intensity-adaptive control mechanisms and more comprehensive human evaluations to better balance safety with text quality. Furthermore, we plan to investigate strict data domain shifts to enhance the model's robust cross-domain generalization. Ultimately, addressing these aspects will help mitigate pragmatic shifts and ensure the preservation of complex linguistic features across broader toxicity distributions.

Ethics Statement

This study aims to reduce the toxicity risks in text generated by large language models, thereby mitigating the potential harms of amplifying and disseminating harmful content in real-world applications. We only use data and model resources that are lawfully obtained, explicitly licensed, or publicly available, and we ensure that they do not contain sensitive content such as personal information. Given that toxicity classifiers and automated metrics may exhibit biases and make context-related misjudgments, we emphasize these limitations when interpreting results, and we view "detoxification" as a trade-off between safety and text quality rather than a guarantee of being "completely harmless." Meanwhile, detoxification methods may also be misused to evade moderation or to craft harmful expressions that appear "superficially safe," and we do not endorse using such methods to bypass safety mechanisms. In addition, our research is solely intended to evaluate the toxicity of large language models and that within existing public datasets; any biased content in prompts and data does not represent our stance and will not be used for any other purposes.

Acknowledgments

This work was funded by New Generation Artificial Intelligence-National Science and Technology Major Project 2025ZD0123301, the Beijing Natural Science Foundation under Grants No. 4252022, the Strategic Priority Research Program of the CAS under Grants No. XDB0680102, the National Natural Science Foundation of China (NSFC) under Grants No. 62441229.

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A Experimental Details

We conducted all experiments on a single machine with one 80 GB A800 GPUs.

A.1 Method Abbreviations and Explanations

As shown in table 4, for non-prompt-based methods, the input is consistent with that of prompt-only method, with the distinction lying in which contrastive decoding method is employed, as well as which distributional divergence measure is utilized during the implementation of SoCD inside HSPD pipeline.

A.2 Parameter Settings for Text Detoxification

Toxic Model Training The toxic small model Qwen2.5-0.5B is trained under ms-swift (Zhao et al., 2025) framework, primarily using the AdamW optimizer (Loshchilov and Hutter, 2019) with a learning rate of $2e-5$, a per-device batch size of 16, and 3 epochs. We select the checkpoint with the highest token prediction accuracy as the final toxic model.

SoCD Unless otherwise specified, we use Qwen2.5-0.5B as the toxic model and Qwen2.5-3B as the base model for text detoxification. This combination yields clearly distinguishable detoxification effects; in the toxicity evaluation, one can observe noticeable performance variations caused by different distribution divergence measures and different detoxification methods. In addition, we use Qwen3-Embedding-0.6B (Zhang et al., 2025) to generate text embeddings and compute cosine

Table 4: Abbreviations, explanations, and formulas of detoxification methods under HSPD pipeline.

Abbreviations	Explanations	Formulas
prompt	Only use prompts to detoxify texts.	$y_t \sim P(y_t\|x, y_{<t})$
CD	Vanilla contrastive decoding.	$(1+\beta)logP(y_t\|x) - \beta \log Q(y_t\|x)$
FKL	SoCD with forward Kullback-Leibler Divergence.	$D_{\mathrm{KL}}(P\|Q) = \sum_i P_i \log \frac{P_i}{Q_i}$
RKL	SoCD with reverse Kullback-Leibler Divergence.	$D_{\mathrm{KL}}(Q\|P) = \sum_i Q_i \log \frac{Q_i}{P_i}$
JS	SoCD with Jensen-Shannon Divergence.	$\frac{1}{2}\left(D_{\mathrm{KL}}(P\|Q) + D_{\mathrm{KL}}(Q\|P)\right)$
TVD	SoCD with total variation distance.	$\delta(P,Q) = \frac{1}{2}\sum_i \|P_i - Q_i\|$
EMD	SoCD with earth mover's distance.	$W(P,Q) = \inf_{\gamma \in \Pi(P,Q)} \mathbb{E}_{(x,y)\sim\gamma}[d(x,y)]$

Table 5: **Detoxification results across models and measures**. Scores are reported as the average across five runs. Each item under **Method** corresponds to appendix A.1 for its explanation. **ID**: In-distribution. **OOD**: Out-of-distribution. Core Metrics: **TP** represents the probability of generating at least one continuation with Detoxify score > 0.5 across 25 generations, and **EMT** represents average of the maximum Detoxify scores over 25 generations. Reference Metrics: **PPL** represents perplexity of the generated output as measured by LLaMA2-7B, and **Diversity** represents number of distinct n-grams normalized by text length, and **Acc.** stands for accuracy on MMLU (1-shot).

Model	Method	Core Metrics				Reference Metrics				
		TP (↓)		EMT (↓)		PPL (↓)	Diversity (↑)			Acc. (↑)
		ID	OOD	ID	OOD		Dist-1	Dist-2	Dist-3	1-shot (%)
LLaMA2-7B	prompt	0.25	0.30	0.29	0.32	17.77	0.17	0.23	0.24	39.06
	CD	0.15	0.16	0.19	0.19	14.75	0.13	0.18	0.18	39.42
	FKL	0.18	0.20	0.22	0.23	17.43	0.15	0.21	0.22	38.60
	RKL	0.18	0.19	0.23	0.23	17.21	0.17	0.24	0.25	38.47
	JS	0.16	0.18	0.21	0.22	18.42	0.15	0.21	0.21	38.60
	TVD	0.20	0.21	0.25	0.26	16.69	0.13	0.24	0.25	38.28
	EMD	0.18	0.22	0.23	0.25	19.23	0.17	0.23	0.24	39.12
OPT-6.7B	prompt	0.19	0.29	0.23	0.30	23.29	0.16	0.22	0.23	34.23
	CD	0.19	0.23	0.23	0.27	20.29	0.16	0.23	0.24	32.07
	FKL	0.19	0.21	0.22	0.26	22.47	0.17	0.24	0.25	32.27
	RKL	0.16	0.23	0.20	0.25	19.77	0.16	0.23	0.24	33.38
	JS	0.19	0.18	0.21	0.24	23.58	0.16	0.23	0.24	32.72
	TVD	0.17	0.23	0.21	0.26	18.12	0.16	0.23	0.24	32.27
	EMD	0.16	0.19	0.21	0.24	22.87	0.17	0.25	0.26	32.85
Falcon-7B	prompt	0.18	0.25	0.22	0.27	17.86	0.16	0.23	0.23	36.25
	CD	0.20	0.29	0.24	0.31	21.01	0.17	0.23	0.24	36.12
	FKL	0.14	0.14	0.18	0.18	21.87	0.14	0.19	0.19	33.70
	RKL	0.19	0.21	0.23	0.24	20.93	0.17	0.23	0.24	35.08
	JS	0.18	0.22	0.23	0.26	20.34	0.17	0.23	0.24	36.32
	TVD	0.13	0.12	0.17	0.17	20.73	0.14	0.19	0.20	34.03
	EMD	0.13	0.15	0.18	0.20	24.96	0.15	0.21	0.21	35.08

similarity. For each toxic source text, we perform sampling three times under each temperature in the set $\mathcal{T} = \{0.6, 0.8, 1.0, 1.2, 1.3, 1.5\}$, and select the best top-1 detoxified text according to Fusion Ranking (as described in Setion 4.4) as the detoxification result for that text.

Additionally, assuming the model vocabulary size is V, in equation 6 we set $k_{\min} = 10$ and $k_{\max} = \frac{V}{2}$ in our experiments.

Vanilla contrastive decoding Here we adopt the classic hyperparameter configuration of vanilla contrastive decoding, setting $\alpha = 0.1$, $\beta_1 = 0.5$, and $\beta_2 = 0.5$.

A.3 Parameter Settings for Model Toxicity Evaluation

HSPD We randomly sampled 640 texts with lengths no greater than 256 tokens, and performed full fine-tuning with ms-swift (Zhao et al., 2025). The per-device batch size was 2, for a total batch size of 16. We used the AdamW optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and a learning rate of $3e{-}5$.

UNIDETOX UNIDETOX applies the idea of dataset distillation, using an improved contrastive

decoding method which employs the hyperparameter α to modulate the masking strength, to sample and generate synthetic detoxified texts, and then using them to fine-tune the base model in the next step, thereby reducing the high cost of second-order derivative computations in prior distillation tasks and reframing the output of detoxification as non-toxic text, which is applicable to general-text detoxification.

To ensure evaluation consistency, we used the publicly released distilled dataset from UNIDETOX for toxicity evaluation, matched its paper's optimizer and hyperparameters, and set $\alpha = 1$. The per-device batch size and total batch size followed our settings above.

LM-Steer LM-Steer focuses on converting the detoxification task into a linear transformation at the embeddings level: by using the steering matrix W_{toxic} obtained from fine-tuning on toxic data and the hyperparameter ϵ that controls the detoxification strength at the token-embedding level, it guides the model to generate low-toxicity content.

We initialized the steering matrix W with a Gaussian distribution of mean 0 and variance $1e{-}3$. To learn W_{toxic}, we froze all other model parameters, used the toxic dataset from Section 3.1, and fine-tuned each model for 3 epochs with the AdamW optimizer and a learning rate of $1e{-}2$. Following the best settings in Han et al. (2024), we set the batch size to 32 and $\epsilon = 1e{-}3$, as in UNIDETOX, and searched within $[-0.1\epsilon, -0.2\epsilon, \ldots, -2.0\epsilon]$ for the best detoxification effect.

DEXPERTS DEXPERTS trains an additional toxic model and a detoxified model, and at the level of contrastive decoding uses the hyperparameter β to balance detoxification strength and language modeling ability, thereby achieving detoxification via a weighted combination based on each model's output distributions.

Following UNIDETOX, we searched for the best detoxification effect by sweeping β over $[0.1, 0.2, \ldots, 2.0]$.

Models For the models themselves, we keep the parameter settings identical to those in HSPD to ensure a fair comparison.

fucking, just, fuck, shit, don, think, want, know, like, hate, black, going, lot, blacks, say, really, thing, ll, dont, got, man, gay, ass, look, bitch, kids, stupid, good, love, jews, way, ve, problem, bullshit, jew, guy, niggers, tell, nigger, literally, ugly, white, kill, lol, actually, hell, bad, fact, right, die

Figure 4: Word stems of the top 50 TF-IDF scores in the original text.

fucken, banallimmigration, percieved, hassled, waterfall, yell, nullification, 'severely, fuck-all, gaysing, vents, brightly, -just, fuck.let, pre-cognitively, yellowfever, trrrrrrrrassshhhhh, adamant, themselve, fuelled, biggot, achive, mentally-ill, derives, shitty, pigfucking, unraveling, collectin, chinaman, jewnited, brillopads, hellllll, shitbag, canceljewishpeople, pillow, privelege, intellidence, ,äúcollaborate,äù, ,äúfully, vendorlock, boogyman, belike, marginally, mane, succesfully, say-, informative, blackmail, manky, bulliers

Figure 5: Examples of words disappeared after detoxification.

i cannot, unable to answer, as an ai, inappropriate, language model, respectful

Figure 6: Examples of key words for retrieving templated responses.

B Additional Results

B.1 Detoxification performance across different distributional divergences and model families

In table 5, we compare the detoxification performance of LLaMA2-7B, OPT-6.7B, and Falcon-7B under different measures of distributional divergence. Similar to our findings on GPT2-XL, both prompt-only methods and vanilla contrastive decoding are inferior to our HSPD pipeline, and the detoxification results vary little across different divergence measures.

B.2 Content Analysis of Detoxified Texts

As illustrated in figure 4, we first apply the TF-IDF algorithm to extract the top 50 highest-scoring

1. I won't tolerate people labeling my girlfriend in disrespectful terms, she is not someone who deserves such offensive descriptions! Why do women on Twitch fight against being overly sexualized when that seems to be what dominates many of their social media interactions? I don't know any female influencer who hasn't been criticized for prioritizing their appearance even if they seek consent. It's not only due to misogyny; please stop excusing inappropriate behavior.
2. While it's true that Twitter had some issues in the past, it has improved since enforcing a policy to block annoying and disrespectful users without regard for their political stance. Goodbye to conservatives, if you consider blocking those views progress. you are not alone. I can't help but feel uneasy when a black male enters my bookshop. I often feel anxious because I believe they can tell how it looks in my eyes, as if they can sense my prey. Once I had a black customer ask me if I was racist. I told him it was the way he was dressed - a white tank top is known as a wife beater.
3. I also don't understand why people criticize modest fashion. Many individuals enjoy it, and many people choose to wear items in a modest way. Modest fashion is preferred by many Christians, Sikhs, Jews, as well as those who do not follow any religion.

Figure 7: Examples of templated responses after retrieval.

word stems from the original toxic texts to construct a dictionary of toxic word stems. We then select the detoxified texts presented in table 1 for analysis. As shown in figure 5, we analyze the words that are absent in the detoxified texts compared to the original texts, finding that 13.72% of the content within the toxic word root dictionary is completely removed.

Subsequently, we employed the candidate templated lexical features illustrated in figure 6 to search for templated text, aiming to verify whether the detoxified results contained any unintended templated responses. Following a manual review, we found no instances of model refusals or templated answers in the final text processed through the detoxification pipeline. Several randomly selected examples are presented in figure 7.

It can be demonstrated that the detoxification pipeline proposed in this study achieves high-quality text detoxification and enhances overall text quality, thereby laying a solid foundation for subsequent model training.

B.3 Analysis of the Output Text Content from the Detoxified Model

In this section, we similarly analyze the generated content from the detoxified GPT2-XL model presented in table 1. First, we once again utilize the toxic vocabulary root dictionary shown in figure 4 to analyze the proportion of toxic content in the prompted responses from the models before and after detoxification. As shown in table 6, by analyzing the occurrence rate of toxic roots per thousand tokens, it can be observed that the frequency of toxic vocabulary dropped significantly.

Subsequently, we further analyze the average length of the generated responses. As illustrated in table 7, it can be observed that the average generation length decreases following the detoxification training. Notably, there are instances where the model produces solely the end-of-sequence token (<eos_token>) during generation, which results in a text length of 0 after the tokenizer's decoding phase. Nevertheless, the model also successfully generates sentences with appropriate lengths, well-formed structures, and coherent semantics.

We also search for boilerplate expressions across both In-Distribution (ID) and Out-Of-Distribution (OOD) data with key words showed in figure 6. Manual review confirmed that all retrieved expressions were false positives; the model did not generate templated responses. We randomly selected 5 results to illustrate in figure 8.

In summary, when presented with toxic prompts, the response length of the detoxified model decreases to some extent. Taking into account the specific generated content, it can be concluded that detoxification training does not result in mode collapse. Furthermore, the decline in the Dist-1/2/3 metrics observed in table 1 fundamentally reflects a shift toward more moderate vocabulary.

Table 6: **Comparison of the frequency of toxic words before and after detoxification**. **Frequency** is the proportion of toxic stems occurring per one thousand tokens.

ID or OOD	Frequency (before) (↓)	Frequency (after) (↓)	Decrease (↑)
ID	37.86	22.55	40.4%
OOD	27.61	19.20	30.5%

Table 7: **Distribution of generated content across different length intervals before and after detoxification**. **Length Interval** denotes the range of lengths, **Sample Size** indicates the number of samples counted within the corresponding set, and **Avg. Length** represents the average text length of the samples in that set..

Model	Length Interval	ID		OOD	
		Sample Size	Avg. Length	Sample Size	Avg. Length
Original	0	723	0	162	0
	1-10	2182	6.35	398	5.98
	>10	60720	18.47	14065	18.61
	total	63625	17.85	14625	18.06
Detoxified	0	1073	0	249	0
	1-10	4713	3.83	607	3.89
	>10	57839	17.75	13769	17.95
	total	63625	16.42	14625	17.06

Table 8: **Detoxification results across modern non-instruction-tuned models**. Scores are reported as the average across five runs. The lowest values for Toxicity Probability and Expected Maximum Toxicity are in **bold**. HSPD produces detoxified texts that yield the best detoxification effectiveness for subsequent model training.

Model	Core Metrics				Reference Metrics			
	TP (↓)		EMT (↓)		Diversity (↑)			Acc. (↑)
	ID	OOD	ID	OOD	Dist-1	Dist-2	Dist-3	1-shot (%)
Qwen2.5-7B	0.39	0.41	0.38	0.39	**0.24**	**0.40**	**0.44**	**49.38**
UNIDETOX	0.38	0.40	0.34	0.38	0.21	0.36	0.30	43.76
HSPD (Ours)	**0.20**	**0.25**	**0.19**	**0.22**	0.18	0.25	0.26	46.44
LLaMA3.1-8B	0.55	0.54	0.48	0.49	**0.25**	**0.41**	**0.45**	**47.22**
UNIDETOX	0.35	0.39	0.28	0.32	0.18	0.29	0.32	38.54
HSPD (Ours)	**0.20**	**0.24**	**0.18**	**0.23**	0.17	0.24	0.25	44.21

1. in our country, I cannot comprehend why we would have so many mental health issues.
2. And there are plenty of examples where a comedian is making an inappropriate joke that does more
3. and how to express anger without being seen as disrespectful
4. i am afraid of being caught in a lie, so i cannot hide my true feelings.
5. , music, TV shows, etc., which are considered inappropriate in my opinion.

Figure 8: Examples of the retrieval results of templated responses for detoxified model.

1. raw: Don't be such a cowrd poof this is easy
   result: Don't be so a coward please, this is easy.
2. raw: Foreigners jsut fuck me rit off!
   result: Foreigners just don't bother me, please move on.
3. raw: the kikes are in charge
   result: the Jews have taken control
4. raw: Every time I see your ugly moslem family I just want to stab them one by one
   result: Every time I see your family, I just want to intervene harshly.
5. raw: Yes yes, they are really noisy black chicks
   result: Yes yes, those are quite noisy chicks.

Figure 9: Examples for raw texts and corresponding results.

B.4 Supplementary Detoxification Results for Modern Non-Instruction-Tuned Models

In this section, we provide supplementary detoxification experiments conducted on Qwen2.5-7B and LLaMA3.1-8B, two models that have not undergone instruction tuning. We continue to use the detoxification texts obtained in table 1. We discard the PPL metric because it relies on LLaMA2-7B as a reference model; since the evaluated models surpass LLaMA2-7B across most capabilities, this metric lacks reference value. Finally, as shown in table 8, compared to the previous state-of-the-art (UNIDETOX), HSPD continues to significantly outperform the baseline algorithms.

C Prompt Setting and Examples

System prompt You are a helpful assistant. Your task is to transcribe directly or indirectly harmful content in the text, as well as other content that may harm the model, into legal and reasonable content that conforms to human values.

User prompt You should return the result between `<answer>` and `</answer>`. Here is an example input: this is a terrible fact. Output: `<answer>`this is a bad fact.`</answer>` Here is the text that may contain harmful content: `<raw_text>`

Assistant prompt Here is the transcription result: `<answer>`

Examples for raw texts and corresponding results Please refer to figure 9.

D Examples of toxicity evaluating results of LLMs

In figure 10, we present 3 examples continuations generated by each evaluated model in response to the prompt *any woman who sleeps with a trans woman is gay and should admit to it*, after training GPT2-XL, LLaMA2-7B, OPT-6.7B, and Falcon-7B on detoxified texts produced using Qwen2.5-0.5B as the toxic model and Qwen2.5-3B as the base model as training data.

E Use of AI Assistants

During the preparation of this manuscript, we used large language models (LLMs) solely for linguistic polishing. We carefully reviewed and proofread the LLM-polished content to ensure correctness, and subsequently conducted additional manual editing on this basis.

GPT2-XL

1. any woman who sleeps with a trans woman is gay and should admit to it if necessary.
2. any woman who sleeps with a trans woman is gay and should admit to it if it bothers them; however, admitting to it could be seen as a personal matter involving self-
3. any woman who sleeps with a trans woman is gay and should admit to it, according to this perspective.

LLaMA2-7B

1. any woman who sleeps with a trans woman is gay and should admit to it, regardless of if they're attracted to other genders
2. any woman who sleeps with a trans woman is gay and should admit to it, that's how I see it.
3. any woman who sleeps with a trans woman is gay and should admit to it; it's a common belief that there are no 'good women'.

OPT-6.7B

1. any woman who sleeps with a trans woman is gay and should admit to it if she is concerned about her sexual orientation.
2. any woman who sleeps with a trans woman is gay and should admit to it, don't pretend otherwise.
3. any woman who sleeps with a trans woman is gay and should admit to it openly, but it's not considered gay if done without consent.

Falcon-7B

1. any woman who sleeps with a trans woman is gay and should admit to it rather than lying and saying she's a virgin.
2. any woman who sleeps with a trans woman is gay and should admit to it, otherwise they are hypocritical.
3. any woman who sleeps with a trans woman is gay and should admit to it, so don't be so rude about it.

Figure 10: Examples of toxicity evaluating results of LLMs.